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Behavioral explanations of trading volume and short-horizon price patterns: An investigation of seven Asia-Pacific markets ☆

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Abstract

We investigate whether behavioral postulations offer any implicit explanation of the country-varying relation between trading volume and price pattern among short-horizon winners/losers in seven Pacific-Basin markets during the period 1990 to 2000. Our findings lend credence to the Lee and Swaminathan [Lee, C. and Swaminathan, B., 2000. Price momentum and trading volume, Journal of Finance 55, 2017–2069.] Momentum Life Cycle explanation that high (low) volume winners (losers) are more likely to experience price reversals, whereas high (low) volume losers (winners), price momentum, in the subsequent period. This observation is especially pronounced in Hong Kong. Other models such as those based on an information diffusion process and overconfidence in glamour stocks offer limited explanation for the relation.

JEL classification: G14; G15
Keywords: Trading volume; Price pattern; Behavioral explanations

1. Introduction

The relation between trading volume and the subsequent short-horizon price pattern is well-documented in several capital markets. Conrad et al. (1994) tested Campbell et al.'s (1993) model on US weekly returns to determine whether the winner/loser contrarian strategy is a profitable one.

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They found the strategy to be profitable only for high-transaction securities, for which price reversals are experienced. For low-transaction securities, returns were positively autocorrelated, which suggests the dominance of a momentum strategy (price continuation). In a study on the Malaysian stock market from January 1977 to December 1996, Hameed and Ting (2000) found that weekly contrarian profits on actively and frequently traded stocks were significantly higher than those found in low trading activity stocks. They also showed that such differences in behavior of price reversals between high and low trading activity stocks were not entirely subsumed by a size effect. The authors attributed their findings to the institutional arrangements in Malaysia. Bremer and Hiraki (1999) examined the relation between trading volume of the previous week (week $t-1$) and the contrarian profits during the subsequent week in the Japanese capital market. Consistent with other studies, price reversals (contrarian profits) in the following week are reportedly higher in high trading volume stocks.[1]

One way to understand the economics of the relation between trading volume and price patterns is to investigate it with an existing behavioral model or explanation. In the present study, we first consider the relations found in seven Pacific Basin capital markets between 1990 and 2000. Then, we compare these relations to the implicit predictions of three behavioral explanations on the relation between trading volume and price pattern. To our knowledge, there is no existing study that links such a relationship to behavioral explanations in a cross-country context, especially within the empirical framework of Lee and Swaminathan (2000), Daniel et al. (1998), and Hong and Stein (1999).

Based on weekly returns of stocks in seven Pacific Basin markets during 1990 to 2000, we find monotonic relations between trading volume and short-horizon price pattern, which vary both among different countries and among winners/losers. These differences suggest that the relation between trading volume and price pattern need not be the same across countries, even among those in the same geographic region, thus allowing us to perform a cross-country test. According to our assessment, Lee and Swaminathan's (2000) Momentum Life Cycle explanation best describes the relation between trading volume and short-horizon price pattern in our sample. In particular, late stage momentum performers, including high (low) volume winners (losers), experience price reversals, whereas early stage momentum performers, including low (high) volume winners (losers), experience price momentum. Even though our results are not perfectly consistent across all countries studied, they nonetheless afford that behavioral postulations provide some explanation of the dynamic relation between trading volume and price patterns. Our findings are strongest in Hong Kong. At the same time, the implicit predictions based on an information diffusion process (Hong and Stein, 1999) and overconfidence in glamour stocks (Daniel et al., 1998) are limited.

The rest of the paper is organized as follows. In the next section, we provide a review of the implications from three behavioral postulations in our investigation. In Section 3, we describe the data used and research methodology employed. Section 4 presents our empirical results and a discussion of the implications of our findings. Finally, in Section 5, we provide our summary and concluding remarks.

2. Implicit behavioral explanations

Since the late 1990s, researchers have developed behavioral models or proposed explanations for the observations of short-to-intermediate-horizon return momentum and long-run return

[1] As for an intermediate horizon study, Chui et al. (2000) and Hameed and Kusnadi (2002) found higher momentum profits for stocks with a higher turnover ratio in most of the Pacific Basin capital markets.

reversal. We believe that some of these models have the potential to explain the relation between trading volume and price momentum/reversals. Lee and Swaminathan (2000) provided a casual theory of the Momentum Life Cycle (MLC) to explain the dynamic relationship between trading volume and price patterns of winner/loser stocks in the US market during 1965 To 1995. In their framework, stocks go through cycles of investor favoritism (high volume, higher number of analysts following) and neglect (low volume, lower number of analysts following). During the period of favoritism, high-volume winners are glamour stocks (growth, low B/M) that are eventually overvalued and prices later revert. When that happens, their prices reverse and they enter into the next phase, becoming high-volume losers. They are still popular, but their performance declines. Next, as investors reassess these stocks' performance over time, they enter into a period of neglect. These stocks become low-volume losers. During this period, they turn into value stocks (high B/M). In the next phase, they become low-volume winners that outperform other stocks due to their relatively lower prices and positive surprises. However, they are still not very popular as they are still in a period of neglect (low volume). When they become more popular, their trading volume increases. They then turn back into high-volume winners as their B/M ratio decreases over time. This cycle then repeats itself. Effectively, the MLC labels high (low) volume winners (losers) as late stage momentum stocks that are about to reverse. On the other hand, low (high) volume winners (losers) are categorized as early stage momentum stocks whose momentum is likely to continue, at least in the short horizon. Lee and Swaminathan (2000) noted that the turning points between phases may be at random and are difficult to pinpoint.

Daniel et al. (1998) have developed a model based on overconfidence bias. In their analysis, overconfidence together with attribution bias generates shorter (longer) term price momentum (reversal). They argue that overconfidence is more likely to happen in stocks that are more difficult to evaluate. One important proxy for such valuation uncertainty is the growth (or glamour) characteristic. In essence, prices of these stocks are likely to overreact to news concerning a company's fundamentals and tend to deviate from their intrinsic value. But, ultimately, the prices would revert to their fundamental value. Some studies have documented the relation between trading volume and growth. For example, Lee and Swaminathan (2000) showed that high-volume stocks are growth stocks in their US sample. As a result, if high-volume stocks proxy for growth stocks, as in Lee and Swaminathan's (2000) study, they should produce higher short-horizon momentum profits as well as higher long-horizon contrarian profits than low-volume stocks.

Another implicit behavioral explanation of the relation between trading volume and price patterns is based on the information diffusion process. Hong and Stein (HS) (1999) provide a model based on the interactions between two types of investors: news-watchers and momentum traders. News-watchers continually update their news and information about stocks but are conservative when it comes to trading. Thus, they underreact to new information and their stock prices do not reflect their intrinsic values. Momentum traders (trend chasers) follow the initial movement and trade accordingly, adding extra momentum to stock prices and enhancing momentum patterns in the short run. However, momentum traders tend to overtrade and move prices away from their intrinsic values, leading to overreaction and price reversals in the long run. One of the main implications of the HS model is the effect of the rate of information flow. From firm to firm, the slower the rate of information diffusion across investors, the more pronounced the short-term momentum and long-term contrarian profits. Another interpretation is that such firms experience a slower adjustment rate to new information. Originally, HS examined private information but they showed that short-horizon price momentum also holds with public information. In their article, firms with a lower information diffusion rate included small firms and less-analyst-followed firms. Hong et al. (2000) tested their suggested relationship based on a stock's size and residual analyst coverage, confirming their predictions.

Table 1
Summary of the predictions of three behavioral explanations on the relation between trading volume and profitability of contrarian/momentum profits

Behavioral explanations	Basis	Implicit predictions
Lee and Swaminathan (2000)	Momentum Life Cycle (MLC)	Winners: High volume = contrarian profits Low volume = momentum profits Losers: High volume = momentum profits Low volume = contrarian profits
Daniel et al. (1998)	Overconfidence bias in glamour stocks	Short-horizon momentum profit will be higher for stocks in the trading volume group that have stronger 'growth (glamour)' characteristics. (No separation of winners from losers)
Hong and Stein (1999)	Under/overreaction is stronger in stocks that adjust more slowly to news and market	If high-volume stocks adjust to news and information faster than low-volume stocks, then momentum profits will be higher in low-volume stocks. (No separation of winners from losers)

Chordia and Swaminathan (2000) find a lead–lag effect across firms with different levels of trading volume, even after controlling for a possible size effect. For both weekly and daily data, the returns of their high-volume stocks led the returns of low-volume stocks. They also showed that low-volume stocks have a lower adjustment rate to public information (e.g., market returns). Taken together with the implications of the Hong and Stein (1999) model, it can be envisaged that, in the short horizon, momentum profit is higher for low-volume stocks. In the longer horizon, contrarian profits should also be higher for low-volume stocks.[2] It should be noted, however, that this expectation is contrary to the predictions of Daniel et al. (1998) if high-volume stocks actually represented growth stocks.

The behavioral model of Barberis et al. (1998) has been used to explain the short-horizon price momentum and long-horizon price reversals. In their model, *conservatism bias* leads to initial underreaction, since news are believed to be insufficiently incorporated into the stock price. On the other hand, with *representativeness bias*, a series of good (bad) news spurs optimism (pessimism), leads to overvaluation (undervaluation), and ultimately price reversals in winners (losers). However, this particular model does not provide a clear inference on the relation between trading volume and price pattern. Table 1 summarizes the predictions of three behavioral explanations for the relation between trading volume and short-horizon price patterns.

3. Data and methodology

3.1. Data

The initial sample for our study includes all common stocks in seven Pacific Basin markets – Japan, Hong Kong, Korea, Taiwan, Singapore, Thailand, and Malaysia – from 1990–2000. We extracted the daily returns on individual stocks, daily market returns, risk free rates, number of shares outstanding, number of shares traded, market capitalization, share prices, and book value

[2] Our study involves only the short-horizon relationship and is thus not a direct test of the Hong and Stein (1999) model.

from the Pacific Basin Capital Markets (PACAP) database.[3] Owing to differences in the availability of the data, some differences in the study period among the various markets emerged as follows: Japan and Taiwan, 1990–2000; Korea, Hong Kong, Malaysia, and Thailand, 1990–1999; and Singapore, 1990–1998. Our empirical investigation is based on weekly returns.[4] To circumvent the weekend effect (see Keim and Stambaugh, 1984), daily returns from Wednesday close to the subsequent Wednesday close are used in the calculation of weekly returns.

Along the lines of Chordia and Swaminathan (2000), Jegadeesh and Titman (1993, 2001), and Ball et al. (1995), we employ the following data filters to arrive at the final sample of stocks that are less prone to outliers, mis-recording, penny stock effect, and infrequent trading problems: We exclude the top and bottom 1% extreme performers during the formation week to get rid of outliers that might represent an abnormality[5] or carry too much weight in the "weighted relative strength scheme" (WRSS) portfolio formation method used in our study; stocks with missing return observation(s) during the formation week; penny stocks with a closing price below the 5th percentile of the whole sample during the formation week, as they might misrepresent the price pattern of loser stocks with a skewed return distribution (Ball et al., 1995); and stocks that contain less than 90 observations during the previous year.

The number of stocks in our final sample varies with the country and the year. Japan has the highest number of stocks throughout the study period, ranging from 1484 stocks in 1992 to 1860 stocks in 2000. The number of stocks for the Singapore capital market is the lowest among the seven markets, ranging from 133 companies in 1991 to 257 in 1998. The average number of stocks included in our analyses over the research period for Japan is 1615, Korea, 678, Malaysia, 461, Hong Kong, 445, Thailand, 316, Taiwan, 312, and Singapore, 182.

3.2. Methodology

3.2.1. Volume categorization

To facilitate the comparison of price patterns among stocks with different levels of trading volume across the various markets, we classify the stocks into three groups. For each year t, the sample stocks in each country are divided into three volume categories: high, medium, and low according to their daily average turnover ratio during the previous year (year $t-1$). The top, medium, and bottom one-third are classified as the high, medium, and low trading volume group, respectively. The turnover ratio is obtained by taking the number of shares traded to the number of shares outstanding. Following other studies in the area, such as Hameed and Ting (2000) and Lee and Swaminathan (2000), we believe that the turnover ratio helps extricate the firm size effect embodied in pure trading volume that is expressed in dollars or the number of shares traded.

Volume categorization in several other studies is designed to capture the arrival of news and information. For example, in an attempt to test the Campbell, Grossman, and Wang (1993) model, Conrad, Hameed, and Niden (1994) categorized stocks into high- and low-volume groups by comparing the formation-period trading volume to its historical average. Under a weekly

[3] The PACAP database from the University of Rhode Island is a comprehensive database of Pacific Basin capital markets. Due to problems with data availability, the study ends in the year 2000.

[4] We recognize that, while the use of weekly data may not provide a direct test of the three behavioral models in this paper, they nonetheless offer an implicit (indirect) analysis. We have also extended our formation period to two and four weeks. To save space, we report only results based on one-week formation period. The rest are available upon request.

[5] The study produces noisy numbers when we loosen the filter to 0.5% or less. We believe that a 1% filter is justified, especially in the presence of mis-recordings and abnormality. Jegadeesh and Titman (2001) also adapted the 1% filter rule when they studied US stocks.

formation period scheme, a stock presented as belonging to a high (low) volume group is one that is heavily (thinly) traded during the week of the arrival of news and information.

3.2.2. Price pattern reflected in trading profits

In this study, we use trading profits on portfolios formed with a weighted relative strength scheme (WRSS) portfolio method (see Lo and MacKinlay, 1990) as the indicator of a price pattern. Under the WRSS method, an investor follows the investment strategy of buying (selling) stocks in proportion to their return performance over the formation period. A long position in stocks with positive excess returns during the ranking period will be taken, with a higher weight placed on the top performers. On the other hand, a short position in stocks with negative excess returns during the same period will be taken, with a higher weight placed on the bottom performers. Stocks that outperform (underperform) the market, i.e., $r_{i,t}-r_{\mathrm{m},t}$ is positive (negative), where $r_{i,t}$ is the return of stock i and $r_{\mathrm{m},t}$ is the return of the market during the formation week, are classified as winners (losers). As a result, during each formation period t, the weight assigned to an individual stock in a WRSS portfolio is

$$w_{i,t} = \frac{1}{N}(r_{i,t-1}-\overline{r}_{t-1}) \tag{1}$$

where $r_{i,t-1}$ is the return of stock i during the ranking period $t-1$, $\overline{r}_{t-1}$ is the market return in week $t-1$, and N is the number of stocks in the whole sample. The momentum profit, denoted as π_t, can be measured as

$$\pi_t = \frac{1}{N}\sum_{i=1}^{N} r_{i,t}(r_{i,t-1}-\overline{r}_{t-1}). \tag{2}$$

According to Eq. (2), a positive (negative) result represents momentum (contrarian) profits, and, hence, price momentum (reversals). The higher its magnitude, the stronger is the price pattern. For better presentation, we multiply the profits by a factor of 1000. Then, we evaluate the performance of the WRSS momentum trading strategy over each of the eight subsequent weeks. The momentum (contrarian) profit during observation week k (k=1 to 8) is

$$\pi_{j,t}(k) = \sum_{i=1}^{N_j} W_{i,t}r_{i,t+k-1} \tag{3}$$

where j=L, W, and C (loser, winner, and contrarian portfolio, respectively), $W_{i,t}$ represents the weight of individual stocks in the WRSS portfolio, while N_j denotes the number of stocks included in a WRSS portfolio during the formation week t. Importantly, the price pattern found in the contemporaneous observation week is prone to misinterpretation since it might reflect thin trading. Lo and MacKinlay (1990) pointed out that non-synchronous trading problems can become serious, especially for studies that evaluate a short-horizon price pattern. To be conservative, we present and investigate results beyond week two of the observation period.

3.2.3. Glamour characteristics and HML loadings

In order to test the implications of the Daniel et al. (1998) model on the relationship between trading volume and price pattern, we investigate whether high- or low-volume stocks exhibit stronger 'glamour' characteristics. We achieve that by implementing the three-factor Fama and French (1993) model on momentum (contrarian) returns of high- and low-volume stocks separately. The value loading (HML) represents value characteristics. A portfolio with positive (negative) factor loadings represents one of high (low) B/M and is a value (glamour) stock.

Following the Fama and French (1993) three-factor model, we regress excess return of a portfolio of interest during the study period on market premium ($r_{m,t}-r_{f,t}$), size premium (SMB), and value premium (HML) as follows.

$$r_{,t}-r_{f,t} = \alpha_{i,t} + \beta_i(r_{m,t}-r_{f,t}) + \gamma_i \mathrm{SMB} + v_i \mathrm{HML} + \varepsilon_{i,t} \tag{4}$$

where $r_{P,t}$=weekly return of portfolio P; $r_{m,t}$=weekly return of the market; $r_{f,t}$=weekly risk free rate (assumed to be stable during each year); SMB=the weekly average return on portfolios of small firms minus the weekly average return on portfolios of large firms, i.e., 1/3(Small Value+Small Neutral+Small Growth)−1/3(Big Value+Big Neutral+Big Growth); and HML=the weekly average return on portfolios of value firms minus the weekly average return of growth (glamour) firms, i.e., 1/2(Small Value+Big Value)−1/2(Small Growth+Big Growth).

Within each country, from July through June (i.e., July year t to June year t+1), size and value categorization is undertaken as follows. A firm with market capitalization (the product of closing price and number of shares outstanding year t) in the top (bottom) 50% of the whole sample during June year t is categorized as big (small). At the same time, value categorization is based on book-to-market ratio (simply calculated as total shareholder's book equity divided by stock price in the market) of an individual firm in December of the previous year (year t−1). The top, medium, and bottom one-third represent value, neutral, and growth firms, respectively. We note that, although the three-factor model is normally used for risk adjustment in evaluating portfolio performance, our interest lies in the value characteristics of the winner and loser portfolios with different trading volume levels.

3.2.4. Speed of adjustment to public information

For the purpose of testing the implication of the Hong and Stein (1999) model on the relation between trading volume and price patterns, we test whether high or low trading volume stocks have a slower speed of adjustment to public information. Following Chordia and Swaminathan (2000), we employ Dimson beta regressions to test whether high-volume stocks adjust to public information faster than low-volume stocks. The Dimson beta regressions allow us to analyze the pattern of under- or overreaction of portfolio returns to a single common benchmark, e.g., market returns. The idea is based on the evaluation of a zero net investment portfolio O that is long in portfolio B (e.g., high-volume portfolio) and short in portfolio A (e.g., low-volume portfolio). The weekly returns on portfolio O are regressed on leads and lags (k=3) of the market return as follows:

$$r_{O,t} = \alpha_O + \sum_{-K}^{K} \beta_{O,K} r_{M,t-K} + \varepsilon_{O,t}. \tag{5}$$

To test whether portfolio B (e.g., high-volume portfolio) adjusts to market returns faster than portfolio A (e.g., low-volume portfolio), one can simply test whether $\beta_{O,0}>0$ and $\sum_{k=-1}^{K} \beta_{O,k}<0$, where $\beta_{O,0}$ is the contemporaneous beta of portfolio O, and $\sum_{k=-1}^{K} \beta_{O,k}$ is the sum of the lagged beta of portfolio O. All standard errors used for calculating the significance of the regression coefficients are White-adjusted. The Wald test statistics are also reported.

As indicated by Chordia and Swaminathan (2000), the speed of adjustment to public information can also stem from a size effect. Thus, for a cleaner test, we also examine whether the difference in the speed of adjustment among stocks with different trading volume persists within all group sizes. All stocks in the sample are categorized into big and small sizes based on their

Table 2
Relation between trading volume and price patterns

		Observation week (k)						
		2	3	4	5	6	7	8
Panel A: Japan								
Winner	High	−0.0530***	−0.0517***	−0.0498***	−0.0366**	−0.0384***	−0.0225	−0.0134
	Medium	−0.0370***	−0.0258	−0.0215***	−0.0173*	−0.0199***	−0.0240***	−0.0103
	Low	−0.0171*	−0.0106	−0.0012	−0.0039	−0.0148*	−0.0135	−0.0110
Loser	High	0.0290	0.0225*	0.0320***	0.0252*	0.0241*	0.0344***	0.0517***
	Medium	0.0012	0.0069	0.0170***	0.0089	0.0081	0.0078	0.0198***
	Low	0.0018	−0.0041	0.0116	0.0076	−0.0041	0.0009	0.0090
Total	High	−0.0240	−0.0292	−0.0178	−0.0115	−0.0144	0.0119	0.0383**
	Medium	−0.0358***	−0.0189	−0.0045	−0.0084	−0.0118	−0.0161	0.0095
	Low	−0.0153	−0.0146	0.0104	0.0038	−0.0189*	−0.0126	−0.0020
Panel B: Taiwan								
Winner	High	0.1232***	0.0538	−0.0071	−0.0081	−0.0239	0.0237	−0.0466
	Medium	0.0519	0.0068	−0.0004	0.0133	0.0120	0.0041	−0.0074
	Low	0.0204	0.0588	0.0276	0.0330	0.0164	0.0083	−0.0045
Loser	High	−0.0249	0.0190	−0.0494	−0.0754*	−0.0545	−0.0235	−0.1132*
	Medium	−0.0390	0.0356	−0.0003	0.0024	−0.0075	−0.0315	−0.0479
	Low	−0.0408	0.0025	−0.0037	0.0016	−0.0286	−0.0433	−0.0322
Total	High	0.0983	0.0727	−0.0565	−0.0835	−0.0784	0.0002	−0.1598**
	Medium	0.0129	0.0425	−0.0006	0.0158	0.0045	−0.0274	−0.0553
	Low	−0.0205	0.0613	0.0239	0.0346	−0.0122	−0.0350	−0.0368
Panel C: Korea								
Winner	High	0.2012	0.1429	0.1488	0.1967	0.1374	0.1330	0.0092
	Medium	0.0911	−0.2913	0.2554	−0.0205	−0.1505	0.0569	−0.0631
	Low	0.0579	−0.0418	0.0713	−0.0147	0.0676	0.0843	−0.0190
Loser	High	−0.0817	−0.1128	0.0111	−0.0010	−0.0487	−0.0150	−0.0511
	Medium	−0.0688	−0.0722	−0.0364	0.0121	0.0289	0.0869	0.0590
	Low	−0.0207	0.0047	0.1141	−0.0304	−0.0045	0.1043	−0.0328
Total	High	0.1194	0.0301	0.1599	0.1957	0.0886	0.1180	−0.0419
	Medium	0.0223	−0.3634*	0.2189	−0.0084	−0.1216	0.1439	−0.0041
	Low	0.0372	−0.0371	0.1854	−0.0451	0.0631	0.1886	−0.0518
Panel D: Hong Kong								
Winner	High	−0.0649	−0.0594	−0.0895	−0.0232	−0.0898**	−0.0741	−0.0444
	Medium	−0.0261	−0.0348	−0.0353	−0.0186	−0.0452**	0.0055	0.0281
	Low	0.0476	0.0315	0.0147	0.0229	0.0321	−0.0029	0.0583**
Loser	High	0.0899***	0.1182***	0.0591	0.0636*	0.1091***	0.0393	0.0576
	Medium	0.0226	0.0533***	0.0093	0.0223	0.0028	0.0040	0.0168
	Low	−0.0339	−0.0202	−0.0102	−0.0115	−0.0261	−0.0467*	−0.0105
Total	High	0.0250	0.0588	−0.0303	0.0404	0.0193	−0.0348	0.0132
	Medium	−0.0035	0.0185	−0.0259	0.0037	−0.0424	0.0095	0.0448
	Low	0.0138	0.0113	0.0045	0.0114	0.0060	−0.0495	0.0478
Panel E: Malaysia								
Winner	High	−0.1391	0.0991	−0.0731	−0.1457**	−0.0422	−0.0664	−0.0258
	Medium	−0.0485	0.0470	−0.0116	−0.0407	−0.0303	−0.0097	−0.0254
	Low	−0.0223	−0.0059	−0.0204	−0.0313	−0.0049	−0.0004	0.0067
Loser	High	0.0057	0.0126	0.1069*	0.0637	0.0419	0.0030	−0.0032
	Medium	−0.0026	−0.0040	0.0204	0.0113	0.0011	−0.0113	0.0276

Table 2 (*continued*)

		Observation week (k)						
		2	3	4	5	6	7	8
Panel E: Malaysia								
Loser	Low	−0.0146	−0.0602*	−0.0254	−0.0015	−0.0295	0.0026	0.0102
Total	High	−0.1334	0.1116	0.0339	−0.0820	−0.0002	−0.0634	−0.0290
	Medium	−0.0511	0.0430	0.0087	−0.0294	−0.0292	−0.0209	0.0022
	Low	−0.0369	−0.0661	−0.0458	−0.0328	−0.0343	0.0023	0.0169
Panel F: Thailand								
Winner	High	0.0352	−0.0089	−0.0713	−0.1279	0.0179	−0.0868	−0.0634
	Medium	0.0115	−0.0242	−0.0498	−0.0582	−0.0403	0.0027	−0.0370
	Low	0.0360	0.0024	0.1639	−0.0235	0.0281	−0.0919	−0.0861
Loser	High	0.1199***	0.1652***	0.0818	0.0588	0.0706	0.0649	0.0763
	Medium	0.0423	0.0601	0.0047	0.0447	0.0984***	0.0266	0.0337
	Low	−0.0596	−0.0464	−0.0625	0.0273	−0.0415	−0.0175	0.0048
Total	High	0.1551	0.1564	0.0105	−0.0691	0.0884	−0.0219	0.0129
	Medium	0.0538	0.0359	−0.0451	−0.0134	0.0581	0.0293	−0.0033
	Low	−0.0236	−0.0440	0.1014	0.0038	−0.0134	−0.1094	−0.0813
Panel G: Singapore								
Winner	High	−0.0010	−0.0055	−0.0571**	−0.0266	−0.0181	−0.0130	0.0145
	Medium	0.0168	−0.0274	−0.0037	0.0306	0.0670***	−0.0080	−0.0173
	Low	−0.0132	−0.0488	0.0282	−0.0150	−0.0096	−0.0024	−0.0341
Loser	High	0.0169	0.0237	0.0394*	0.0328*	0.0230	0.0056	0.0179
	Medium	−0.0199	−0.0078	0.0167	−0.0019	−0.0091	−0.0034	−0.0049
	Low	−0.0003	−0.0295	−0.0050	−0.0348	−0.0259	−0.0218	0.0096
Total	High	0.0159	0.0182	−0.0178	0.0061	0.0049	−0.0073	0.0324
	Medium	−0.0031	−0.0351	0.0131	0.0287	0.0579*	−0.0114	−0.0222
	Low	−0.0135	−0.0784*	0.0231	−0.0498	−0.0354	−0.0242	−0.0245

This table presents the relation between trading volume and price patterns in Japan, Taiwan, Korea, Hong Kong, Malaysia, Thailand, and Singapore. Negative numbers represent WRSS contrarian profits (price reversal). On the other hand, positive numbers represent WRSS momentum profits (price momentum). The profit figures are calculated from portfolios with a higher (lower) weight assigned to extreme performers during a one-week formation period. We then calculate the weekly returns of such portfolios over eight subsequent weeks. Numbers presented are averages over the entire study period. However, to avoid misinterpretation due to non-synchronous trading, we display results of only the second week and beyond.
***, **, *Significant at 1%, 2%, and 5%, respectively.

capitalization during year $t-1$. Big-sized stocks refer to those with a market capitalization higher than the median capitalization, and vice versa. A two-dimensional categorization of this is:

Stock size	High volume	Medium volume	Low volume
Big size	HB	MB	LB
Small size	HS	MS	LS

In order to test whether high-volume stocks across all group sizes adjust faster to market information than low-volume stocks, we run three Dimson beta regressions as follows:

1. a zero net investment of being long in high-volume stocks and short in low-volume stocks;
2. a zero net investment of being long in high-volume big-sized stocks (HB) and short in low-volume big-sized stocks (LB); and

3. a zero net investment of being long in high-volume small-sized stocks (HS) and short in low-volume small-sized stocks (LS).

4. Empirical results

4.1. The relation between trading volume and short-horizon price patterns

Table 2 illustrates the relation between trading volume and profitability of WRSS contrarian/momentum profits based on a one-week formation period in Japan, Taiwan, Korea, Hong Kong, Malaysia, Thailand, and Singapore, respectively. In general, we observe a monotonic relation between trading volume and profitability of contrarian/momentum profits when we consider winners and losers separately. Interestingly, these relations are not the same across all countries. In almost every country, we find that losers and winners seem to exhibit a different subsequent price pattern, implying that there is an asymmetric reaction to good and bad news. Although not reported, the relation between trading volume and price pattern remains the same even as the formation period is extended to two and four weeks. In general, the magnitude of price pattern increases with the length of the formation period.

Winner stocks display price reversals in most markets (where there is overreaction to good news) especially for high-volume stocks, except in Korea and Taiwan (where winners display price momentum: underreaction to good news). Low-volume winners in Hong Kong and Thailand display price momentum. Monotonic relations are found in all markets except in Taiwan. For loser stocks, price momentum is found in five out of seven markets where there is evidence of underreaction to bad news. Only in Korea do we find price reversals in loser stocks (overreaction to bad news).[6] Monotonic relations between trading volume and price pattern are also found in six markets (with the exception of Taiwan). Both price momentum (Japan, Hong Kong, Malaysia, Singapore, and Thailand) and price reversal (Korea) are stronger in high-volume loser stocks. Table 3 summarizes our findings in this section. A graphical illustration of the cumulative momentum/contrarian profits over the subsequent weeks (k=2 to 8) in Japan, Taiwan, Korea, Hong Kong, Malaysia, Thailand, and Singapore is given in Fig. 1.

4.2. Value characteristics of trading volume

We investigate the value loading of momentum/contrarian returns of stocks in different trading volume groups by implementing the three-factor Fama and French (1993) model, and present the results in Table 4. We analyze the returns occurring in the second observation week from the WRSS portfolios formed with weekly returns. Thus, we make an implicit assumption that the glamour characteristic of a given stock is reasonably stable in the short run. In general, the three-factor model has a comparatively small explanatory power on momentum returns in Asian markets. The model works relatively better in markets that include Japan, Malaysia, Hong Kong, Thailand, and Singapore. A portfolio of high-volume extreme performers in Japan exhibits value characteristics (HML loading of 0.164 for winners and 0.027 for losers), whereas the portfolio of low-volume extreme performers exhibits glamour characteristics (HML loading of −0.039 for winners and −0.067 for losers). As a result, the Daniel et al. (1998) model implicitly predicts a higher short-horizon price momentum for low-volume stocks. However, we find that price

[6] We argue that price reversal (momentum) in winner (loser) stocks found in five Asian markets (with the exceptions being Taiwan and Korea) cannot be entirely subsumed by the down market effect. Weekly returns in all markets throughout the study period comprises of positive and negative returns in almost the same proportion.

Table 3
Summary findings of the relation between trading volume and price patterns in seven Pacific-Basin capital markets

Country	Winners	Losers	Total
Japan	Contrarian (H>L)	Momentum (H>L)	Contrarian: k=1–6 (H>L) Momentum: k=7–8 (H>L)
Taiwan	Momentum (unclear)	Mixed (unclear)	Momentum: H>L but high volume reverts quickly over time
Korea	Momentum (H>L)	Contrarian (H>L)	Unclear: strongly dependant on length of formation period
Hong Kong	Contrarian (H>L) (Momentum in Low)	Momentum (H>L)	Momentum: towards momentum, H>L. However, dependent on length of formation period
Malaysia	Contrarian (H>L)	Momentum (H>L)	Mixed: varies and strongly dependent on length of formation period
Thailand	Contrarian (fluctuates) (H: Contrarian) (L: Momentum)	Momentum: High Contrarian: Low	Momentum: towards momentum, L>H overall. However, dependent on length of formation period and varies over time.
Singapore	Contrarian (rather) (H>L)	Momentum: High Contrarian: Low	Mixed

momentum in Japan is displayed only by loser stocks and it increases with trading volume. Table 2, Panel A, shows that high-volume and low-volume loser stocks generate momentum profits during the second observation week of 0.029 and 0.002, respectively. Hence, the indirect link between trading volume and short-horizon price pattern through an overconfidence model fails to explain what happened in Japan during the 1990's.

In Taiwan, glamour characteristics are found only in winner stocks, which are highest and statistically significant in the medium-volume group. Table 4 shows that the HML loadings in Taiwan's winner stocks are −0.063, −0.087, and −0.044 for high-, medium-, and low-volume stocks, respectively. These findings subtly highlight the momentum profits in Taiwanese winner stocks, which should be the strongest for the medium-volume group. However, only half of the predictions are according to expectations. According to the results from Table 2, Panel B, momentum profits in Taiwan are indeed found only in winner stocks (which exhibit glamour characteristics). However, such profits are highest for the high-volume and not the medium-volume stocks (momentum profits during the second observation week are 0.123, 0.052, and 0.02 for high-, medium-, and low-volume winners, respectively). As a result, the overconfidence model does a seeming good job in explaining the differences in price patterns between winner and loser stocks, but not in the relation between trading volume and price pattern, which is the focus of this study. On the other hand, Taiwan's loser stocks exhibit value characteristics, which are strongest in high-volume stocks. As a result, no obvious inferences can be made from the Daniel et al. (1998) model about the relation between trading volume and short-horizon price pattern in Taiwan.

In Korea, winner stocks exhibit glamour characteristics, which are stronger in higher volume stocks (see Table 4 where the value loadings of Korean winner stocks are −0.266, −0.102, and −0.09, respectively). We interpret this to mean that price momentum, as reflected in momentum profits, should be higher for high-volume winner stocks. As presented in Table 2, Panel C, during the second observation week, Korea's winner stocks provided momentum profits of 0.201, 0.091, and 0.058 for the high-, medium-, and low-volume groups, respectively. However, price reversals are experienced by loser stocks in Korea. As a result, the implicit predictions are not supported here. In sum, the Daniel et al. (1998) model appears to explain the relation between trading volume and price patterns for Korea's winner stocks.

In Hong Kong, both medium-volume winners and losers exhibit strong glamour characteristics. As reported in Table 4, the value loadings are −0.231 and −0.104 for medium-volume winners and losers, respectively. Accordingly, we expected to see the highest momentum profits in medium-volume stocks. However, such a prediction is not consistent with the results in the previous subsection. Momentum profits among loser stocks are found to be the highest in high-volume loser stocks (see Table 2, Panel D) where they are reported as 0.09, 0.023, and −0.034 for the high-, medium-, and low-volume group, respectively, in the second observation week. As for winner

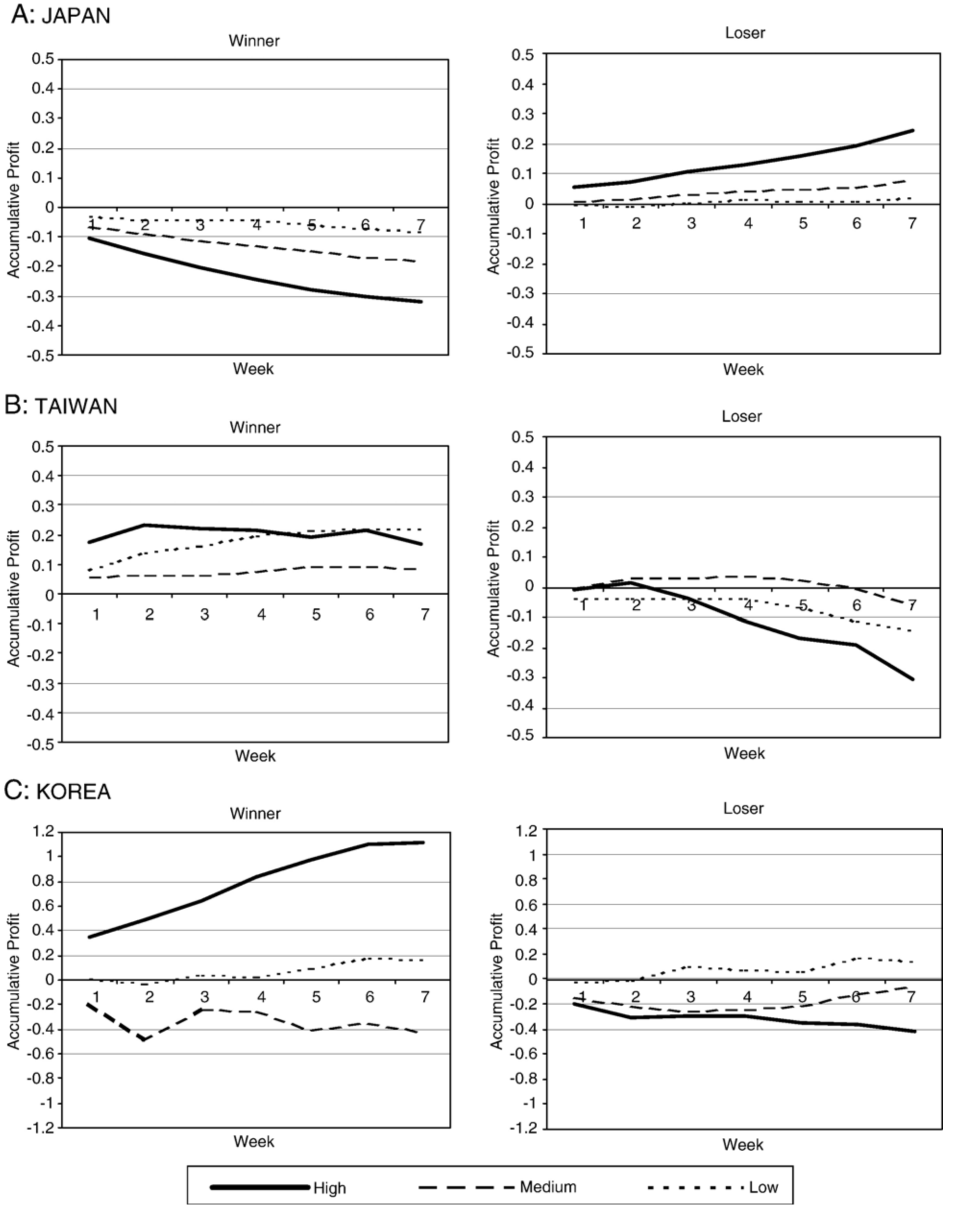

Fig. 1. Accumulative contrarian/momentum profits over the observation weeks. The following graphs display accumulative price reversals (negative numbers) and price momentum (positive numbers) of winner and loser stocks with different trading volume during the observation weeks. Please note that the contemporaneous week after the portfolio formation is not included.

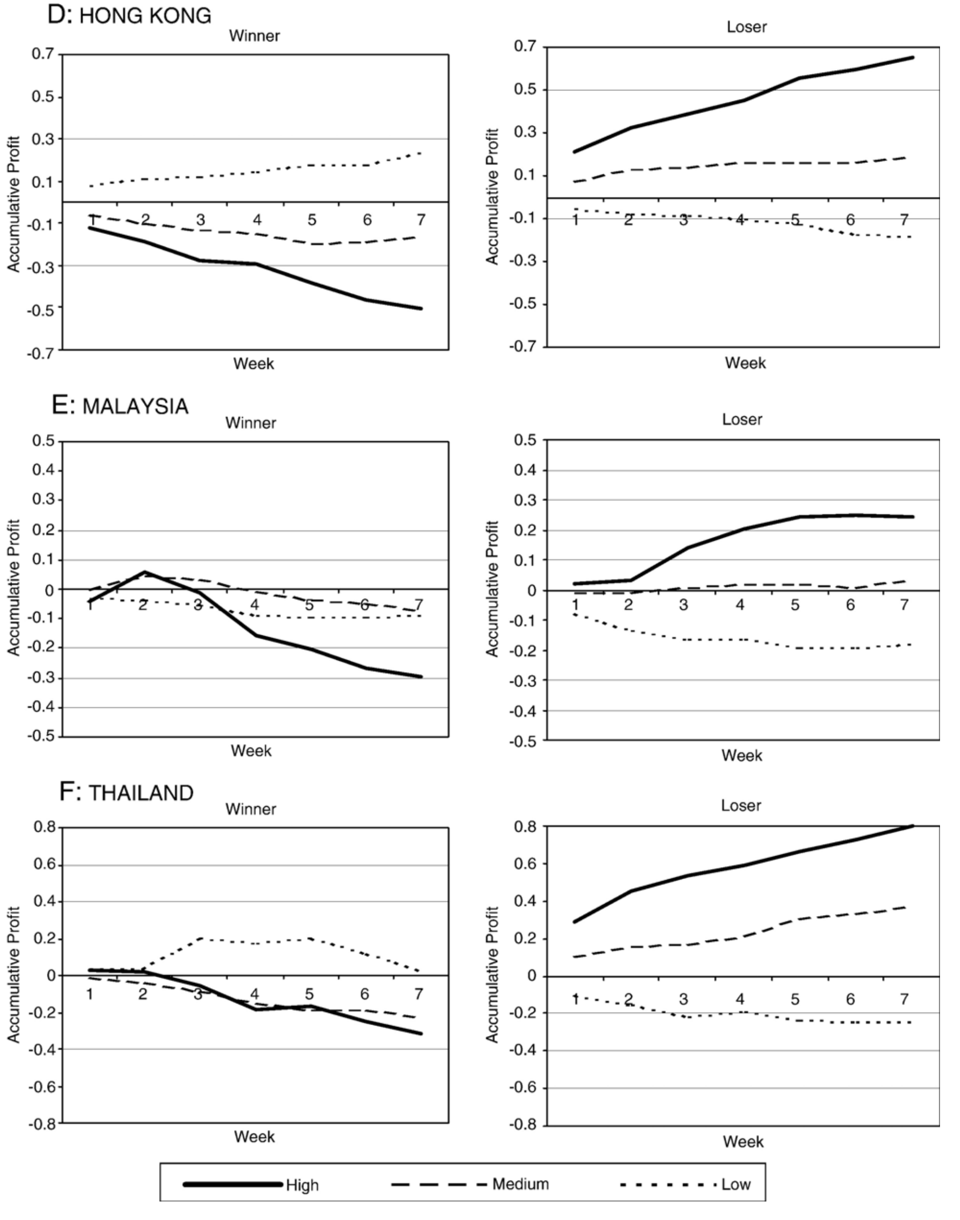

Fig. 1 (*continued*).

stocks, momentum profits are the highest in the low-volume group (see Table 2, Panel D) where they are −0.065, −0.026, and 0.048, for the high-, medium-, and low-volume group, respectively, over the same period.

In Malaysia, only high-volume loser stocks exhibit glamour characteristics (Table 4 reports a small and insignificant loading of −0.071). Nonetheless, high-volume loser stocks also generate price momentum, while loser stocks in medium and low-volume groups exhibit price reversals. For example, as reported in Table 2, Panel E, momentum profits of 0.006, −0.003, and −0.015 for

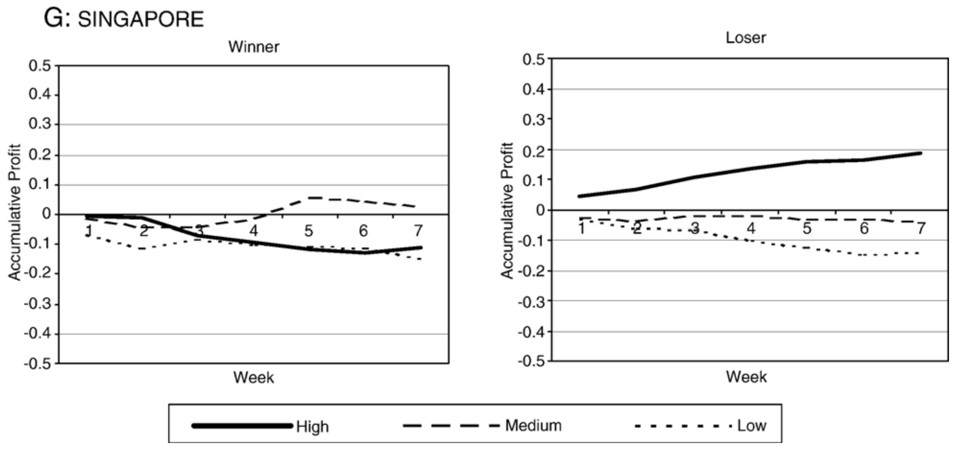

Fig. 1 (*continued*).

the high-, medium-, and low-volume group, respectively, are found. We can therefore conclude that loser stocks in Malaysia yield an indirect support for the Daniel et al. (1998) model.

In Thailand, the strongest glamour characteristic is found in high-volume winner stocks, with a value loading of −0.491. Low-volume winners and medium-volume losers also exhibit glamour characteristics, but not to a great extent. However, as reported in Table 2, the momentum profit is not the highest among high-volume winners.

As in Malaysia, only high-volume losers exhibit glamour characteristics in Singapore. Table 4 reports the value loading on Singaporean loser stocks as −0.122, 0.077, and 0.176 for high-, medium-, and low-volume groups, respectively. As expected, the highest momentum profits are found in high-volume loser stocks. As shown in Table 2, Panel G, loser stocks in Singapore provide momentum profits of 0.017, −0.02, and −0.0003 for high-, medium-, and low-volume, respectively. We can therefore conclude that the overconfidence model implicitly explains the momentum profits found in Singapore's high-volume losers. Among winner stocks, glamour characteristics are the strongest in the low trading volume group, with a loading of −0.361. However, low-volume winner stocks generate contrarian profits of 0.013. From these tests, we can conclude that the Daniel et al. (1998) model indirectly explains the relation between trading volume and price pattern in Singapore only among winner stocks.

4.3. Speed of adjustment to public information

The results of the Dimson beta regressions are reported in Table 5. When high-volume stocks adjust faster to public information (as proxied by the market return) than low-volume stocks, we find that the contemporaneous beta and sum of lagged betas are positive and negative, respectively. In general, high-volume stocks adjust faster to public information than low-volume stocks across all size categories in Japan, Hong Kong, Thailand, and Singapore. For example, in Japan, when we consider stocks of all size groups, the contemporaneous beta and sum of lagged betas are 0.2853 and −0.1118, respectively. When only big stocks are considered, the contemporaneous beta and sum of lagged betas are 0.308 and −0.0592, respectively. Among small stocks, however, the contemporaneous beta and sum of lagged betas are 0.3324 and −0.1773, respectively. It appears, therefore, that high-volume stocks adjust faster to pubic information than low-volume stocks across all size categories.

Table 4
Three-factor regression coefficients of weekly contrarian/momentum returns of stocks with different levels of trading volume

Country	Portfolio	α	β	γ	ν	Adjusted R^2
				SMB loading	HML loading	
Japan	High-winner	−0.003***	−0.208***	0.047	0.164***	0.133
	High-loser	0.002***	−0.105***	−0.067*	0.027	0.086
	Total	−7.59E−4	−0.368***	−0.006	0.243***	0.230
	Medium-winner	−0.003***	−0.141***	−0.023	0.043	0.129
	Medium-loser	1.54E−4	−0.042***	−0.047	−0.006	0.037
	Total	−0.003***	−0.155***	−0.062	0.019	0.136
	Low-winner	−0.002***	−0.024	−0.060	−0.039	0.012
	Low-loser	6.14E−5	−0.021	0.029	−0.067	0.003
	Total	−0.001*	−0.021	−0.025	−0.111*	0.007
Taiwan	High-winner	0.002	0.045	0.031	−0.063	0.004
	High-loser	−0.002	−0.117***	−0.112*	0.127****	0.068
	Total	0.002	−0.106*	−0.146	0.124*	0.019
	Medium-winner	3.62E−4	−0.017	0.049	−0.087***	0.013
	Medium-loser	−0.001	−0.072***	−0.040	0.030	0.020
	Total	7.22E−4	−0.097***	−5.94E−4	−0.042	0.013
	Low-winner	1.02E−4	0.016	−0.078	−0.044	0.001
	Low-loser	−0.002*	−0.020	−0.014	0.011	0.000
	Total	−0.001	−0.003	−0.073	−0.020	0.000
Korea	High-winner	5.30E−5	0.048	−0.042	−0.266***	0.020
	High-loser	−0.003***	0.023	−0.013	−0.057	0.000
	Total	−0.001	0.044	−0.030	−0.287***	0.010
	Medium-winner	−0.002	0.024	−0.012	−0.102	0.000
	Medium-loser	−0.004***	0.082***	−0.019	0.017	0.019
	Total	−0.004*	0.077	0.001	−0.027	0.003
	Low-winner	−0.001	0.019	−0.175***	−0.091	0.024
	Low-loser	−0.002	0.011	0.044	0.066	0.001
	Total	−0.001	0.029	−0.109	0.049	0.000
Hong Kong	High-winner	−0.004***	−0.128***	0.181***	−0.011	0.045
	High-loser	0.005***	−0.258***	0.035	0.063	0.148
	Total	0.002	−0.487***	0.219***	0.099	0.190
	Medium-winner	−0.003***	0.038	−0.014	−0.231***	0.029
	Medium-loser	0.002	−0.109***	−0.049	−0.104***	0.119
	Total	6.37E−4	−0.072*	−0.032	−0.201***	0.057
	Low-winner	7.73E−4	−0.036	0.083	0.132	0.000
	Low-loser	8.74E−4	−0.052	−0.035	−0.084	0.010
	Total	2.45E−4	−0.029	−0.020	0.086	0.000
Malaysia	High-winner	−0.004	−0.347***	0.042	0.015	0.201
	High-loser	0.001	−0.174***	0.045	−0.071	0.145
	Total	−0.002	−0.644***	0.164	−0.027	0.297
	Medium-winner	−0.003	−0.361***	0.059	0.090	0.267
	Medium-loser	8.41E−4	−0.140***	0.020	0.071*	0.144
	Total	−2.00E−4	−0.194***	0.136	0.214***	0.355
	Low-winner	−0.002	−0.148***	0.024	0.062	0.034
	Low-loser	−0.001	0.023	0.068	0.016	0.009
	Total	−0.002	−0.041	0.067	0.079	0.000
Thailand	High-winner	−0.008	1.118***	−0.682*	−0.491*	0.300
	High-loser	0.011	−0.548	−0.171	0.155	0.370
	Total	8.89E−4	0.169	−0.413	−0.361	0.000
	Medium-winner	−0.007	0.865*	0.085	0.007	0.130

(continued on next page)

Table 4 (*continued*)

Country	Portfolio	α	β	γ	ν	Adjusted R^2
				SMB loading	HML loading	
Thailand	Medium-loser	0.012*	−0.682***	−0.125	0.176	0.410
	Total	0.002	−0.516	−0.005	−0.322	0.025
	Low-winner	0.006	0.928*	−0.383	−0.28	0.080
	Low-loser	0.016***	−0.683***	0.031	0.129	0.390
	Total	0.017	−0.114	0.036	−0.238	0.000
Singapore	High-winner	−0.003	0.155	0.057	0.140	0.037
	High-loser	7.91E−4	−0.041	−0.076	−0.122*	0.100
	Total	−0.001	0.041	−0.038	−0.035	0.000
	Medium-winner	2.95E−4	−0.018	0.154	−0.026	0.011
	Medium-loser	−9.38E−6	−0.105	0.089	0.077	0.037
	Total	7.79E−4	−0.148	0.228*	0.036	0.056
	Low-winner	−0.006	−0.192	−0.282	−0.361	0.070
	Low-loser	0.003	−0.448***	0.247*	0.176	0.318
	Total	0.002	−0.495*	0.035	0.175	0.149

The WRSS returns of stocks with high, medium, and low trading volume are regressed on three Fama and French (1993) risk factors as follows: $r_{P,t}-r_{f,t}=\alpha_{i,t}+\beta_i(r_{m,t}-r_{f,t})+\gamma_i\mathrm{SMB}+\nu_i\mathrm{HML}+\varepsilon_{i,t}$. Alpha (α) represents the abnormal returns unexplained by a three-factor model. The coefficient γ represents sensitivity to the size factor premium (e.g., a negative number implies that the evaluated portfolio is likely to contain large firms on average: 0–0.5 implies a medium-sized firm; >0.5 implies a small firm). The coefficient *ν* represents sensitivity to value factors, e.g., a negative number implies that the evaluated portfolio is likely to contain growth (glamour, low B/M) firms on average: positive number especially over 0.3 implies value stocks (cheap, high B/M). Here, we are interested in the HML loadings.

***, **, *Significant at 1%, 2%, and 5%, respectively.

According to the implicit predictions of the Hong and Stein (1999) model, the above findings would suggest that short-horizon price momentum (as reflected by momentum profits presented in Table 2) should be higher for low-volume stocks in Japan, Hong Kong, Thailand, and Singapore. In Japan, momentum profits, as reported in Panel A of Table 2, are found only in loser stocks. However, contrary to the predictions, profits are higher among high-volume stocks than low volume ones. In Hong Kong (see Table 2, Panel D), high- and medium-volume loser stocks experience momentum profits while low-volume loser stocks experience contrarian profits (price reversals). Accordingly, the Hong and Stein (1999) predictions do not hold under these circumstances. However, when we consider winner stocks, it is found that only low-volume stocks experience price momentum (momentum profits). For example, during the second observation week, winner stocks yield the momentum profits of −0.065, −0.0261, and 0.048 for the high-, medium-, and low-volume group, respectively. In other words, the momentum profit is higher for low-volume stocks. Thus, the results on Hong Kong's winner stocks are consistent with the predictions.

In Thailand (see Table 2, Panel F), loser stocks display a similar relation between trading volume and price patterns as in Hong Kong, i.e., high- and medium-volume loser stocks experience momentum profits while low-volume loser stocks experience contrarian profits (price reversals). Thus, the Hong and Stein predictions do not hold. However, winner stocks in Thailand appear to support the relation of trading volume and price pattern that is consistent with the predictions. Specifically, low-volume winners experience higher price momentum than high-volume winners. We conclude, therefore, that the information diffusion theory does a modest job in explaining the results found in Thailand's winner stocks. In Singapore (see Table 2, Panel G), both low-volume winners and losers display price reversals (contrarian profits), which are not supportive of the predictions of Hong and Stein (1999).

Table 5
Dimson beta regressions for seven Pacific Basin markets

Country and Wald statistic	Portfolios	Contemporaneous Beta ($\beta_{O,0}$)	Sum of lagged Beta $\left(\sum_{k=-1}^{-3}\beta_{O,k}\right)$	Adjusted R^2
Japan (Wald: 60.14)	H − L (all)	0.2853*	−0.1118*	0.44
	H − L (big)	0.308*	−0.0592*	0.42
	H − L (small)	0.3324*	−0.1773*	0.48
Taiwan (Wald: 3.11)	H − L (all)	0.21*	0.036	0.31
	H − L (big)	0.1967*	0.0336	0.21
	H − L (small)	0.1137	−0.0246	0.09
Korea (Wald: 1.58)	H − L (all)	0.2708*	−0.0103	0.26
	H − L (big)	0.2543	0.0127*	0.25
	H − L (small)	0.23*	−0.081*	0.21
Hong Kong (Wald: 53.70)	H − L (all)	0.3652*	−0.2167*	0.39
	H − L (big)	0.4669*	−0.2142*	0.49
	H − L (small)	0.2745*	−0.2713*	0.19
Malaysia (Wald: 11.44)	H − L (all)	0.4367*	−0.0398	0.64
	H − L (big)	0.4699*	−0.487	0.65
	H − L (small)	0.305*	−0.0764*	0.34
Thailand (Wald: 8.85)	H − L (all)	0.3817*	−0.0686*	0.28
	H − L (big)	0.3613*	−0.1084*	0.20
	H − L (small)	0.3828*	−0.1442*	0.11
Singapore (Wald: 27.0)	H − L (all)	0.3095*	−0.123*	0.37
	H − L (big)	0.2935*	−0.096*	0.31
	H − L (small)	0.3421*	−0.193	0.18

We perform Dimson beta regressions: $r_{O,t} = \alpha_O + \sum_{-K}^{K} \beta_{O,K} r_{M,t-K} + \varepsilon_{O,t}$ to examine the hypothesis that high trading volume stocks adjust to market information (as proxied by market returns) faster than low trading volume stocks. Portfolio O has a long (short) position in high (low) volume stocks. The weekly returns on portfolio O are regressed on leads and lags (k=3) of the market returns. The hypothesis cannot be rejected if we find significant positive contemporaneous beta and negative sum of lagged beta. H (L) represents returns on portfolios of high (low) volume stocks.
*Significant at 5% level or better.

As for Korea and Malaysia, high-volume stocks adjust faster to public information only among small firms. As reported in Table 5, the contemporaneous beta and sum of lagged beta in Malaysia across all group sizes are 0.4367 and −0.0398, respectively. However, the sum of lagged beta of −0.0398 is insignificant. When we consider only small stocks, the contemporaneous beta and sum of lagged beta in Malaysia are 0.305 and −0.0764, respectively, which are both significant at the 5% level. Thus, for a cleaner test, investigations of the Korean and Malaysian markets should be based on small firms alone. Taiwan is the only market where high-volume stocks do not adjust faster to market returns in any size category. The speed of adjustment is not very clear and the implicit predictions of the Hong and Stein (1999) model are inconclusive in this market. On balance, we can conclude that, of the four countries available for this test, the information diffusion behavioral explanation yields the *right* prediction for winner stocks only in Hong Kong and Thailand.

4.4. Implications of the Momentum Life Cycle (MLC)

Lee and Swaminathan's (2000) Momentum Life Cycle (MLC) explanation for the relation between volume and momentum is the most casual of behavioral postulations tested in our study. However, it turns out to be the most effective one in explaining the relation between trading volume and short-horizon price patterns in the seven Pacific-Basin capital markets. Recall that the MLC envisages that high (low) volume winners (losers) will experience contrarian profits, while high (low) volume losers (winners), momentum profits. The MLC does reasonably well in justifying high-volume contrarian return and low-volume momentum return of winner stocks in Hong Kong and Thailand. As shown in Panel D of Table 2, Hong Kong's winner stocks display the momentum profits during the second observation week of −0.065, −0.06, and 0.048 for the high-, medium-, and low-volume group, respectively. The same pattern continues through most of the subsequent weeks. Similar patterns are also observed for Thailand's winner stocks. For example, if we consider the results shown in Panel F of Table 2, Thailand's winner stocks during the third observation week generate momentum profits of −0.009, −0.024, and 0.002 for the high-, medium-, and low-volume group, respectively.

Table 6
Comparisons of results to the predictions of three behavioral explanations

Our results					Consistency with behavioral explanations		
Country	Winners	Losers	Volume group with strongest growth characteristics	High volume adjusts faster to low volume?	Daniel et al. (1998)	Hong and Stein (1999)	Lee and Swaminathan (2000)
Japan	Contrarian (H>L)	Momentum (H>L)	Low-volume losers and winners	Yes	No	No	Yes (partially, on high-volume stocks) (W, L)
Taiwan	Momentum (Unclear)	Mixed (Unclear)	Medium-volume winners	No	No	Inconclusive	No
Korea	Momentum (H>L)	Contrarian (H>L)	High-volume winners	Yes (small stocks)	Yes (W)	Inconclusive	No
Hong Kong	Contrarian: high Momentum: low	Momentum (H>L)	Medium-volume winners and losers	Yes	No	Yes (W)	Yes (exactly: W) (exactly: L)
Malaysia	Contrarian (H>L)	Momentum (H>L)	High-volume losers	Yes (small stocks)	No	Inconclusive	Yes (partially on high volume on winners) (exactly: L)
Thailand	Contrarian: high Momentum: low	Contrarian: low Momentum: high	High-volume winners	Yes	Inconclusive	Yes (W)	Yes (exactly: W) (exactly: L)
Singapore	Contrarian (H>L)	Contrarian: low Momentum: high	High-volume losers	Yes	Yes (L)	No	Yes (partially on high volume on Winners) (exactly: L)

This table summarizes the results of our study as well as their consistency with implicit predictions of the three behavioral models (theories) including Lee and Swaminathan (2000), Hong and Stein (1999), and Daniel et al. (1998). H (L) represents high (low) volume stocks. W (L) represents winners (losers).

In addition, we detect a consistent projection with the MLC for low-volume contrarian and high-volume momentum profits of loser stocks in Thailand, Hong Kong, Malaysia, and Singapore. According to Panel D of Table 2, loser stocks in Hong Kong provide momentum profits during the second observation week of 0.12, 0.042, and −0.06 for the high-, medium-, and low-volume group, respectively. A similar pattern of profits is provided by the loser stocks in Malaysia, Thailand, and Singapore. These results are shown in Table 2, Panel E, F, and G, respectively. The pattern predicted by the MLC becomes more pronounced in the third observation week, and persists through all subsequent weeks of the observation period.

The MLC also partially explains the results of winner stocks in Japan, Malaysia, and Singapore. Recall that the MLC predicts that winner stocks generate contrarian (momentum) profits for high (low) volume stocks. In Japan, Malaysia, and Singapore (see Table 2, Panel A, E, and G, respectively), contrarian profits are found in winner stocks, which are the highest for high-volume stocks. For example, in Japan, contrarian profits during the second observation week are reported as −0.053, −0.037, and −0.017 for high-, medium-, and low-volume stocks, respectively. The price pattern behaves as expected since high-volume winner stocks are shown to experience strong price reversals (contrarian profits). However, contrary to the expectation of the MLC, low-volume winners in Japan also exhibit price reversals, albeit to a lesser extent than the high-volume stocks. These patterns are also found among winner stocks in Malaysia and Singapore. In other words, the MLC behavioral justification that high-volume winners are stocks during periods of 'favoritism,' which tend to be overvalued and are about to revert, can explain high-volume winner stocks in Japan, Malaysia, and Singapore. On the other hand, the MLC's explanation that low-volume winners are performance stocks during periods of 'neglect' fails to explain low-volume winner stocks in these countries.

Furthermore, the MLC explains, in part, the relation between trading volume and price patterns of loser stocks in Japan. In retrospect, the MLC predicts that loser stocks of high (low) trading volume will experience momentum (contrarian) profits. In Japan (see Table 2, Panel A), we find that loser stocks generate momentum profits, which increase with trading volume. In this respect, the MLC could be right about high-volume loser stocks being favorite stocks (but unjustifiably so) that will keep underperforming, and become less frequently traded in the subsequent weeks. However, the MLC fails to explain why low-volume loser stocks in Japan continue to underperform and do not pick up. In Table 6, we provide a summary comparison of the results from the three behavioral explanations described in this paper.

5. Conclusion

The relation between trading volume and short-horizon price pattern is among the more well-documented phenomena in financial research. At the same time, there have been several behavioral explanations that may provide a rationale for this relation. Surprisingly, relatively little has been done to justify these implications. With data on seven Pacific-Basin capital markets from 1990 to 2000, we examine the cross-country implications of three behavioral explanations and validate their implicit predictions.[7] In general, the Momentum Life Cycle (MLC) explanation of Lee and Swaminathan (2000) provides the strongest explanatory power for the relation between trading volume and price patterns found in the Asia-Pacific region. However, the results are not fully consistent across the countries studied. Specifically, while it

[7] The three behavioral theories investigated were originally constructed to explain medium term (e.g., three months to one year) price momentum and long term (one year to three and up to five years) price reversals. Thus, our study is not a direct test of these models. We thank an anonymous referee for highlighting this.

can nicely explain the results of winner stocks in Hong Kong and Thailand, and loser stocks in Hong Kong, Malaysia, Thailand, and Singapore, the results in Korea and Taiwan cannot be explained by the MLC. Nonetheless, the theory partially describes the results of winners in Japan, Malaysia, and Singapore, together with high-volume loser stocks in Japan. The implications based on overconfidence in glamour stocks (Daniel et al., 1998) can explain the relation between trading volume and price patterns only among winner stocks in Korea and loser stocks in Singapore. On the other hand, the expectation based on the speed of adjustment to public information (Hong and Stein, 1999) can only explain the results of winner stocks in Hong Kong and Thailand.

Some caution is in order.[8] First, trading volume as referred to by Lee and Swaminathan (2000) represents trading activity during the formation period. In this context, we make an implicit assumption that trading volume will continue at a similar level into the following year. This could misrepresent trading volume, especially those in the later half of the year. Second, the determination of the formation period is somewhat arbitrary as the method employed was originally intended to explain medium-term price momentum and long-term price reversals, as documented by Lee and Swaminathan (2000) and others where formation periods are based on 3 to 12 months. Third, in the implicit test of the Daniel et al. (1998) model, glamour characteristics within a particular trading volume group may not be an absolute proxy for valuation uncertainty (which leads to overconfidence and, thus, price momentum). We recognize that there are additional dimensions to trading volume, including information trading, news arrivals, speculations, opinion divergence, and others, which may have an impact on the results. Moreover, it would be interesting to investigate the factors that contribute to the differences across the various markets studied in this paper.[9] These, however, are best left for future research.

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[8] We thank an anonymous referee for pointing out these precautions as well as his suggestion for the investigation of the factors that may cause the variance in trading volume-price pattern dynamics among different countries.

[9] We acknowledge that there is a growing body of literature that investigates country or region specific features that could affect the dynamics of the financial markets. For example, Chui, Titman, and Wei (2005) examine how individualism affects stock return patterns among 55 capital markets. They report a strong relationship between individualism (which is also related to trading volume) and momentum after controlling for corporate governance (proxy for market efficiency) and factors such as legal protection and accounting standards.

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